Investor Sentiment for Real Assets: The Case of Dry-Bulk Shipping Market *

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Abstract. We investigate the role of sentiment and its implications for real assets. Using shipping sentiment proxies that capture market expectations, valuation and liquidity, we construct sentiment indices for the dry-bulk shipping market. Evidence suggests that sentiment affects the monthly returns of real assets. The empirical findings also show that market sentiment serves as a contrarian indicator for future cycle phases in all sectors. Further, a sentiment-based trading simulation exercise on the sale and purchase of vessels shows that investors can benefit from higher returns compared to the buy-and-hold benchmark, while partially offsetting the highly volatile nature of the shipping industry.

Keywords: investor sentiment, real assets, cycles, trading strategies

JEL Classification: G11, G15, C13

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1. Introduction

The impact of investor sentiment on the valuation of asset prices is an issue that has attracted the interest of academics and practitioners alike. To a certain extent, discrepancies between observed assets prices and their expected discounted present value are often attributed to investor sentiment (Shleifer and Vishny, 1997). In this paper, we present evidence that investor sentiment can also have a significant effect on the tangible assets of an economy, such as in the market for the sale and purchase of second-hand vessels. Our interest in this market stems from the importance of shipping to the world economy - since approximately 90% of world trade is transported by sea according to the International Maritime Organization - and its effectiveness as a global economic activity indicator (Kilian, 2009).

A number of studies provide empirical evidence on the role of investor sentiment in the stock markets. Baker et al. (2012) construct global and local sentiment indices and show that all indices are contrarian predictors of cross-sectional stock market returns. Stambaugh et al. (2012) explore the role of sentiment in a broad set of anomalies in cross-sectional returns and find that its predictive power is higher during high-sentiment periods. Berger and Turtle (2012) find that portfolios with opaque firm characteristics offer the greatest marginal performance when previous sentiment levels are at their lowest. Yu and Yuan (2011) examine the influence of investor sentiment on the market's mean-variance trade-off and show that expected excess return is positively related to conditional variance only in low-sentiment periods. Baker and Wurgler (2006, 2007) construct sentiment indices for the U.S. stock market and show that sentiment has larger effects on stocks whose valuation is highly subjective and difficult to arbitrage. Furthermore, low sentiment is related to subsequent higher returns for particular categories of stocks (such as, young, high volatility, unprofitable, non-dividend-paying, extreme growth, and distressed). Lemmon and Portniaguina (2006) study the relationship between investor sentiment and small-stock premium and find that sentiment forecasts the returns of small and low institutional ownership stocks. Further, Brown and Cliff (2004) investigate sentiment and its relation to short-term stock market returns. They report that sentiment levels and changes are correlated with market returns, although the predictive power for stock returns is small. Finally, Huan (2008) finds that institutional investor sentiment, measured by the bull-bear spread, relates to the prices of SPX options.

Prior literature (Barberis et al., 1998; Brown and Cliff, 2004; Baker and Wurgler, 2007) suggests that there is a broad range of variables measuring sentiment. For example, Baker and Wurgler (2006) and Baker et al. (2012) use market price-based proxies, such as closed-end fund discounts, IPOs volume and their first-day returns, volume turnover, equity share of new issues, dividend premium and volatility premium. Other studies employ micro-trading data; Wang (2001) employs trading positions of large speculators, large hedgers and small traders in the US futures markets, whereas Kumar and Lee (2006) and Barber et al. (2009) use respectively broker data and transaction data. In addition, investor surveys (Lee et al., 2002; Brown and Cliff, 2004; Menkhoff and Rebitzky, 2008) and consumer confidence indices (Lemmon and Portniaguina, 2006; Schmeling, 2009) are also employed as proxies for sentiment. Finally, investor sentiment has been linked to close-end fund discounts (Neal and Wheatley, 1998; Swaminathan, 1996).

Given that the current literature is mainly devoted to the use of sentiment in explaining stock returns, we extend these studies by examining, for the first time, the role of sentiment and its implications for real assets, i.e., vessels. We employ proxies that reflect participants' beliefs about market expectations, asset valuation and liquidity in the shipping market, and construct sentiment indices for the capesize, panamax, handymax and handysize sectors[1] as well as the overall dry-bulk shipping market.

We examine sentiment as a predictor of future vessel price returns and present evidence that sentiment affects the monthly returns on real assets, not only stock market returns as documented in the existing literature. We then investigate the predictive power of sentiment in identifying vessel price cycle phases up to 6 months ahead and find a significant contrarian relationship for market sentiment, while sector-specific sentiment is found to be important only in the panamax sector. Finally, we perform a sentiment-based trading simulation exercise for the sale and purchase of second-hand vessels. Our findings suggest that sentiment-based strategies outperform the passive buy-and-hold strategy significantly by offering higher annualized returns and lower volatility on the investment.

The outline of the paper is as follows. Section 2 describes the sentiment proxies and the construction of the sentiment indices. Section 3 presents the empirical findings of sentiment as a predictor of future vessel price returns and cycle phases. Section 4 illustrates the trading simulation exercise of sentiment as an investment timing tool. Section 5 concludes.

2. Sentiment Indices

[1] Capesize: dry-bulk carriers with a cargo-carrying capacity exceeding 150,000 dwt. These vessels generally operate along long-haul iron ore and coal trade routes. Panamax: vessels with a cargo-carrying capacity of 60,000-99,999 dwt. These vessels carry coal, grains and, to a lesser extent, minor bulks, including steel products, forest products and fertilizers. Handymax: vessels with a cargo carrying capacity of 40,000-59,999 dwt; these operate on a large number of geographically dispersed global trade routes, and carry primarily grains and minor bulks. Handysize (dry-bulk): handysize vessels have a cargo carrying capacity of 10,000-39,999 dwt. Generally, these vessels are versatile in terms of their operating characteristics and carry minor bulk cargoes around the world.

While investor sentiment may refer to as the propensity to trade on noise rather information, it may also refer to investor optimism or pessimism (Antoniou et al., 2013). It is evidenced that individuals with positive (negative) sentiment make optimistic (pessimistic) judgments and selections (Bower, 1981; Wright and Bower, 1992). Measuring sentiment is subjective since there is no consensus on what the appropriate proxies are (Schmeling, 2009). We combine five proxies which in our view reflect the sentiment of participants in the shipping market, in addition to a component of non-sentiment related idiosyncratic variation. We classify our proxies into three main categories: market expectations (net contracting and money committed), valuation (price-to-earnings and second-hand-to-newbuilding vessel price ratios) and liquidity (turnover ratio). Our choice of sentiment proxies is based on the notion that optimism/pessimism about the overall state of the dry-bulk shipping market can affect the decision of investors about the sale and purchase of second-hand or the order of newbuilding vessels. Following Baker and Wurgler (2006) and Baker et al. (2012), we orthogonalize the raw sentiment proxies and then construct total, market and sector-specific sentiment indices using the first principal component method.

2.1 SENTIMENT PROXIES

The first proxy we employ is net contracting (NC); this measures the number of orders for newbuilding vessels which are contracted with shipyards every month in each sector after accounting for order cancellations and vessels being removed from the market for scrapping. The NC proxy is selected by analogy to Baker and Wurgler (2006, 2007) and Baker et al. (2012) use of the number of initial public offerings (IPOs), as the demand for IPOs is said to be extremely sensitive to investor sentiment. Further, according to the behavioural model of Greenwood and Hanson (2013), high shipping earnings are associated with high second-hand vessel prices and high orderbook, but forecast low future returns. They argue that over-investment in new capacity during booms is due to shipowners being overconfident and incorrectly believing that investments will continue to reap high returns; partly due to "competition neglect" by shipowners, caused by the time lag involved in the shipbuilding process (Kahneman, 2011). Hence, the motivation for using the net contracting proxy is twofold; first, we assume that the demand for new vessels in the shipping market resembles the demand for new equity issues in the financial markets and, second, shipping participants tend to follow the herd and invest in new capacity when valuations are generally high. The monthly net contracting is given by:

$$NC_{i,t} = \left(order_{i,t} - order_{i,t-1} + del_{i,t}\right) - scrap_{i,t}, \tag{1}$$

where $order_{i,t}$ is the orderbook, i.e., the number of vessels awaiting construction or being constructed, for sector i and month t, $del_{i,t}$ the number of vessel deliveries, and $scrap_{i,t}$ the number of vessels being scrapped. The first term in Equation (1) provides the monthly change in the orderbook less order cancellations. We then subtract scrapping of vessels to obtain NC. This way our proxy takes into account order cancellations, which reflect investment sentiment and conditions in shipping markets, and thus measures net investment in new capacity. We assume that high-sentiment periods are characterized by high vessel orders with cancellations and scrapping of vessels being at low levels.

The second proxy is the money committed (MC) in the dry-bulk market and is an approximation of the funds committed for the purchase of newbuilding vessels:

$$MC_{i,t} = order_{i,t} \times newPx_{i,t}, \tag{2}$$

where $newPx_{i,t}$ is the price of newbuilding vessels for sector i and month t. Broader measures of financing activity are also used as sentiment proxies. For example, Baker and Wurgler

(2000) suggest that the share of equity issues in total equity and debt issues is a measure of financing activity that can capture sentiment. In the shipping industry, the majority of capital originates from bank finance, where 30% equity to 70% debt is the historical average for a typical shipping project. Therefore, we choose the MC proxy as a measure of financing availability and propensity to provide capital for new shipping investments. We assume that, during freight market booms when sentiment is high, banks are also overconfident in their decisions to provide capital; and they follow their competitors so that they do not lose their market share as capital providers to the shipping industry. Hence, we expect MC to be positively related to investor sentiment.

The third sentiment proxy is the price-to-earnings ratio (PE) for vessels:

$$PE_{i,t} = schPx_{i,t}/earn_{i,t}, \tag{3}$$

where $schPx_{i,t}$ is the price of 5-year old second-hand vessels, and $earn_{i,t}$ the annualized earnings (1-year time-charter rates[2]) in sector i for month t. The PE ratio as a measure of sentiment has been considered previously in the literature and has been found useful in predicting subsequent stock returns (Campbell and Shiller, 1998; Fisher and Statman, 2006; Kurov, 2008). Generally, high PE ratios reflect the relative degree of overvaluation in asset prices. In our case, the estimate of earnings used is forward-looking and reflects the expected earnings from operating the vessel for one year from the point of valuation; we thus expect high PE ratios to be associated with low sentiment levels. For example, if current vessel prices are high relative to the 1-year earnings (i.e., high PE ratio), shipowners expect vessel prices to drop in the future in anticipation of limited earnings growth; hence, sentiment is low.

[2] Fixed daily freight rate, measured in US$/day, received by the shipowner for chartering (leasing or letting-out) a vessel for a 1-year period.

The fourth proxy we consider is the second-hand to newbuilding price ratio (SNB):

$$SNB_{i,t} = schPx_{i,t}/newPx_{i,t}. \tag{4}$$

Newbuilding vessels have longer useful economic lives than identical second-hand vessels of certain age (e.g. five or ten-year old vessels), which in general means are more expensive. However, during prosperous and high sentiment periods, investors prefer to take advantage of the prevailing market conditions immediately; as such, they favour the purchase of second-hand vessels to avoid the time lag in the construction process of newbuildings[3]. This creates an immediate delivery premium which occasionally drives second-hand above newbuilding prices. The selection of SNB as a sentiment proxy is by analogy (inverse) to Baker and Wurgler (2004) use of dividend premium. Dividends are generally perceived by investors as a characteristic for safety (Baker and Wurgler, 2006). When dividends are at premium, companies are more likely to pay them, and less so when they are at discount (Fama and French, 2001). Therefore, companies appear to cater to prevailing sentiment for or against "safety" when deciding about the dividend payments. Similarly, SNB reflects the preference of market agents for second-hand vessels to newbuilding ones and measures the immediate delivery premium, which is related to how optimistic investors feel about the current market conditions.

Our last proxy reflects the relative liquidity in the dry-bulk market. The use of liquidity as a sentiment proxy follows from Baker and Stein (2004) who suggest that liquidity, more specifically turnover, can serve as an investor sentiment index. They argue that, under

[3] The building of new vessels is characterized by significant construction lags. The actual construction time, which is on average 2 years, may often be lengthened considerably by the lack of available berth capacity in shipyards or due to order backlog. For example, Kalouptsidi (2013) quantifies the impact of time-to-build on shipping investments and estimates that the average construction time almost doubled between 2001 and 2008.

short-sales constraints, irrational investors are more likely to participate in the market and add liquidity when they are optimistic. Short-sales constraints are even more important in the shipping markets, as it is difficult and costly for participants to establish short positions on vessels. Baker and Wurgler (2006, 2007) capture market liquidity by the ratio of trading volume to the number of shares listed on the New York Stock Exchange; whereas Baker et al. (2012) use the ratio of total dollar volume over a year to the total capitalization at the end of the previous year. However, liquidity is an elusive notion (Amihud, 2002; Pastor and Stambaugh, 2003) which has been represented by various empirical measures in the literature[4]. Our choice of liquidity measure is driven by data availability at a monthly frequency; therefore, we represent shipping market liquidity in terms of the turnover ratio. The turnover ratio (TURN) measures the activity in the sale and purchase market for second-hand vessels in terms of total number of vessels available in the market:

$$TURN_{i,t} = M^{-1} \sum_{s=t-M+1}^{t} Sale_{i,s}/Fleet_{i,s} \tag{5}$$

where $Fleet_{i,s}$ is the total number of available vessels in sector i and month s, and $Sale_{i,s}$ the number of vessels sold. We anticipate that high turnover periods are related to high sentiment.

The proxies are calculated on a monthly basis for the capesize, panamax, handymax and handysize sectors of the dry-bulk market using data by Clarksons Shipping Intelligence Network for the period February 1996 to January 2012. Since the proxies may embody a component that reflects underlying macroeconomic fundamentals, we remove the non-

[4] Proxies for liquidity, among others, include: i) turnover (Amihud and Mandelson, 1986), ii) dollar volume (Chordia et al., 2001), iii) share volume (Brennan and Subrahmanyam, 1995), iv) Roll implicit spread estimator (Roll, 1984), v) illiquidity ratio (Amihud, 2002), and vi) proportion of zero returns measure (Lesmond et al., 1999).

sentiment part by orthogonalizing the proxies to three macro variables: the G7 monthly industrial production growth and two recession-period dummies for the G7 and Major 5 Asia countries[5], provided by the Organisation for Economic Co-operation and Development (OECD). The chosen macro variables are not related to our proxies resulting in high average correlations between the orthogonalized and raw proxies: 0.87, 0.92, 0.90, and 0.88 for the capesize, panamax, handymax and handysize sectors, respectively. Further, the correlation matrix of orthogonalized proxies indicates marginally higher co-movement compared to the correlation matrix of raw proxies (not presented in the paper). Finally, we de-trend all proxies using the Hodrick-Prescott (1997) filter[6] and use their cyclical component in our analysis.

2.2 TOTAL, MARKET, AND SECTOR-SPECIFIC SENTIMENT INDICES

For each sector we construct a first-stage index comprising 15 loadings given by the current, 1-month lagged and 2-month lagged orthogonalized (denoted by $\perp$) proxies. This way we allow for a lead-lag relationship between the proxies as some of them may reflect a shift in sentiment earlier than others (Brown and Cliff, 2004; Baker and Wurgler, 2006). To decide which proxies will be eventually included in the total sentiment index, we calculate the correlation between the first-stage index and the current and lagged proxies. The proxies with the highest correlation qualify as the final sentiment proxies, and the first principal component of the selected proxies provides the *total sentiment index*:

$$SENTI_{cape,t}^{total^{\perp}} = 0.451NC_{t-2}^{\perp} + 0.439MC_{t}^{\perp} - 0.299PE_{t-1}^{\perp} + 0.506SNB_{t-1}^{\perp} + 0.508TURN_{t-1}^{\perp} \quad (6)$$

$$SENTI_{pana,t}^{total^{\perp}} = 0.362NC_{t-2}^{\perp} + 0.462MC_{t}^{\perp} - 0.350PE_{t-1}^{\perp} + 0.532SNB_{t-2}^{\perp} + 0.499TURN_{t-1}^{\perp} \quad (7)$$

[5] These macro variables are selected by taking into account the global nature of the shipping markets, although we recognize that additional macro factors may also drive our proxies.

[6] In our analysis we use a smoothing parameter of λ=14,000. Different values of λ were also tested with no significant difference in the final estimation of the trend and cyclical components of the series.

$$SENTI_{hmax,t}^{total^{\perp}} = 0.300NC_{t-2}^{\perp} + 0.440MC_{t}^{\perp} - 0.423PE_{t-1}^{\perp} \quad + 0.527SNB_{t-2}^{\perp} + 0.509TURN_{t-2}^{\perp} \quad (8)$$

$$SENTI_{hsize,t}^{total^{\perp}} = 0.407NC_{t-2}^{\perp} + 0.421MC_{t}^{\perp} - 0.433PE_{t-1}^{\perp} + 0.498SNB_{t-2}^{\perp} + 0.471TURN_{t-2}^{\perp} \quad (9)$$

The variance explained by the first principal component in each sector is 52%, 60%, 61% and 62%. Thus, we conclude that most of the proxies' common variation is captured by one factor. Further, the high correlation between the first-stage indices and $SENTI_{i,t}^{total^{\perp}}$ for each sector (ranging from 92% to 97%) suggests that dropping the remaining 10 proxies does not lead to loss of information.

[INSERT TABLE I HERE]

We observe that the sentiment proxies enter the index with the expected sign (see Section 2.1). In addition, MC carries the same time subscript across all sectors and lags all other proxies, whereas the remaining proxies have different time subscripts. Additionally, NC and SNB appear to be the leading proxies. Although the proxies are highly correlated with the total sentiment index on average, there are instances where the correlation between the proxies is relatively low (see Table I). This implies that our proxies contain unique information in reflecting investor sentiment; therefore, the risk of using variables carrying the same information is low.

Table II, Panel A, shows high correlation between the total sentiment indices, which can be attributed to shipping companies operating vessels in more than one sector within the dry-bulk market and as such, sentiment flowing from one sector to another. Therefore, to separate the overall market sentiment from the sector-specific sentiment we construct the *market sentiment index* $SENTI_{t}^{market^{\perp}}$ based on the first principal component of the 4 total sentiment indices ($SENTI_{i,t}^{total^{\perp}}$):

$$SENTI_t^{market^{\perp}} = 0.491SENTI_{cape,t}^{total^{\perp}} + 0.508SENTI_{pana,t}^{total^{\perp}} + 0.513SENTI_{hmax,t}^{total^{\perp}} + 0.488SENTI_{hsize,t}^{total^{\perp}} \qquad (10)$$

[INSERT TABLE II HERE]

Table II, Panel A also illustrates high correlations between the total sentiment and market sentiment indices, implying that little information is lost by $SENTI_t^{market^{\perp}}$. Next, we obtain the *sector-specific sentiment indices* ($SENTI_{i,t}^{sector^{\perp}}$) from the residuals of the regression of $SENTI_{i,t}^{total^{\perp}}$ for each sector on $SENTI_t^{market^{\perp}}$. The correlation between the sector-specific indices appears reduced (Table II, Panel B), suggesting that sentiment within sectors is captured more suitably by $SENTI_{i,t}^{sector^{\perp}}$ than $SENTI_{i,t}^{total^{\perp}}$. The market and sector-specific sentiment indices are plotted in Figure 1, from which it is obvious that market sentiment is smooth, thus capturing market-wide changes. On the other hand, sector-specific sentiment indices move in a more erratic way, i.e., reflecting the idiosyncratic features of each sector.

[INSERT FIGURE 1 HERE]

2.3 VESSEL PRICES TURNING POINTS AND STATISTICS

In this section, we use the non-parametric algorithm of Bry and Boschan (1971) as modified by Harding and Pagan (2002) to date the second-hand vessel prices turning points. This method captures the turning points of vessel prices in an efficient way with a minimum set of assumptions. The key assumptions made in determining the turning points are: i) an initial peak (trough) is located at the highest (lowest) point in the vessel price series using a window of 5 months either side of that point; ii) a peak (trough) must be followed by a trough (peak); iii) a cycle (defined as peak-to-peak or trough-to-trough) must have a minimum duration of 18 months; iv) a phase (defined as peak-to-trough or trough-to-peak) must have a minimum duration of 5 months; and v) turning points are not to be determined within the first or last 5 months of the vessel price series. To identify the turning points, we use data running from January 1976 to January 2012. Here, we report only the turning points (Figure 2) and statistics (Table III) that apply to our sample period February 1996 to January 2012.

[INSERT FIGURE 2 HERE]

As a preliminary accuracy inspection of the selected sentiment proxies and the constructed indices, we plot, in Figure 3, the capesize vessel prices turning points on the market sentiment index. To begin with the troughs, it can be observed that market sentiment coincides with the trough of December 1996, while it lags the remaining troughs by 1 to 4 months. In terms of peaks, market sentiment is a leading indicator on average. It exactly matches the peak of January 1998, declines prior to the peaks of September 2000, April 2005 and July 2008; and lags the peak of April 2010 by 3 months. Overall, there is good correspondence of the market sentiment index to the capesize vessel prices turning points, and during the following episodes: Asian Crisis 1997/98, dot-com bubble 2000/01, and the recent worldwide financial turmoil 2008/09.

[INSERT FIGURE 3 HERE]

The identified turning points and vessel price series are used to produce measures of the average duration ($\widehat{D}_i$), and amplitude of expansions (through to peak) and contractions (peak to trough), ($\hat{A}_i$), for each sector *i,* as defined by Harding and Pagan (2001):

$$\widehat{D}_i = NTP_i^{-1} \sum_{t=1}^{T} S_{i,t}, \tag{11}$$

$$\hat{A}_i = NTP_i^{-1} \sum_{t=1}^{T} S_{i,t} R_{i,t}, \tag{12}$$

where NTP_i is the number of turning points, T is the number of observations, $R_{i,t}$ is the monthly percentage change of second-hand vessel prices, and $S_{i,t}$ the cycle phase; when measuring the duration of expansions, $S_{i,t}$ takes value 1 (0) when in expansion (contraction) and vice-versa in the case of contractions' duration. In addition, we use the concordance statistic by Harding and Pagan (2002) to calculate the proportion of time that the prices of two types, i and j, of vessels are concurrently in the same phase:

$$\hat{I}_{ij} = T^{-1} \left(\sum_{t=1}^{T} S_{i,t} S_{j,t} + \sum_{t=1}^{T} (1 - S_{i,t})(1 - S_{j,t}) \right). \tag{13}$$

To test the null hypothesis of no concordance, we follow Harding and Pagan (2006).

[INSERT TABLE III HERE]

Looking at Table III, Panel A, the capesize, panamax and handysize sectors experience similar average duration of 14-15 (23-24) months from peak-to-trough (trough-to-peak), i.e., expansions last for about 10 months more than contractions. In the case of the handymax sector, an expansion (contraction) lasts for 26.5 (20.5) months, on average. In terms of amplitude (Table III, Panel A), across sectors, panamax and handymax experience the best returns during expansions (63.2% and 67.8% respectively), while they perform the worst in contractions (-58.6% and -62.4% respectively). The capesize sector amplitude stands at 56.8% in expansions and -52.9% in contractions; whereas the handysize sector of smallest cargo-carrying capacity has the lowest gains (22.4%) and losses (-45.8%) during upturns and downturns respectively.

Finally, Table III, Panel B, shows that the concordance index between the dry-bulk sectors is statistically significant. It is evident that the synchronization across the sector pairs is high, e.g., the panamax/handymax and capesize/handysize pairs are synchronized 93.0% and 83.8% of the time respectively. On the whole, synchronization statistics point towards market integration and herd-like behaviour, where the market sentiment may play a major role compared to the sector-specific sentiment.

3. Empirical Results

In what follows, we examine whether sentiment is a statistically significant predictor of vessel price returns and propose a model that uses sentiment as a predictor for future vessel price cycle phases. Further, we assess the fit of the logit model to the cycle chronology identified in Section 2.3. Since the constructed sentiment indices are stationary and highly persistent, they may impute biased coefficient and standard error estimates (Stambaugh, 1999; Ferson et al., 2003). We adjust for these biases and test the robustness of the models by employing the stationary bootstrap method[7] of Politis and Romano (1994). To this end, we

[7] The stationary, instead of the ordinary, bootstrap technique is employed since the latter is only valid in the case of *iid* observations. When the ordinary bootstrap is applied to stationary and persistent variables (in our case the sentiment indices), the re-sampled series will not preserve the statistical properties of the original dataset and will lead to inconsistent results and statistical inference. The stationary bootstrap is based on re-sampling blocks of random length, where the length of each block follows a geometric distribution with mean block length $1/q$. The choice of q depends on the degree of persistence: a large value of q is appropriate for data that exhibit serial dependence and vice versa. The value of q chosen in our experiments is 0.1, corresponding to a mean block length of 10 (for more technical details, see Sullivan et al. 1999).

bootstrap the original dataset to generate 5,000 new time series for the cycle phases and the five sentiment proxies for each sector. Then, we construct the corresponding total, market and sector-specific indices as outlined in Section 2.2. For each bootstrapped time series we re-estimate the OLS and logit models and report the bias-adjusted standard errors.

3.1 PREDICTIVE REGRESSIONS FOR VESSEL PRICE RETURNS

Sentiment has been previously employed in the literature as a contrarian predictor of the cross-section of expected stock returns (Brown and Cliff, 2004; Baker and Wurgler, 2006; Lemon and Portniaguina, 2006, Schmeling, 2009). In a recent study, Baker and Wurgler (2012) construct sentiment indices and find robust predictability of the time series of the cross-section returns for six major stock markets. Since the constructed shipping sentiment indices are categorized into total, market and sector-specific, we run similar regressions to Baker and Wurgler (2012).

First, we regress the monthly vessel price returns for sector i in month $t+1$ on the corresponding total sentiment index in month t, or on the market and sector-specific sentiment indices in month t. We then run regressions for the vessel price cross-section returns:

$$R_{i,t+1} = \beta + \mu SENTI_{i,t}^{total^{\perp}} + u_{i,t+1} \tag{14}$$

$$R_{i,t+1} = \rho + \phi SENTI_{t}^{market^{\perp}} + \omega SENTI_{i,t}^{sector^{\perp}} + u_{i,t+1} \tag{15}$$

[INSERT TABLE IV HERE]

Table IV, Panel A, shows that total sentiment is statistically significant and a contrarian indicator of future vessel price returns, for individual sectors or across all sectors.

For example, a decrease in the capesize total sentiment ($SENTI_{cape,t}^{total^{\perp}}$) by one standard deviation is associated with 1.00 percent/month higher capesize vessel price returns. Further, it appears that market sentiment overshadows sector-specific sentiment and that monthly vessel price returns are mainly affected by market sentiment. For example, a decrease in the market sentiment ($SENTI_t^{market^{\perp}}$) by one standard deviation is associated with 1.08 percent/month higher capesize vessel price returns. The results are in line with Baker and Wurgler (2012) and suggest that the sentiment effect is noteworthy. In particular, market sentiment appears to be significant across all sectors, implying cross-sector sentiment contagion. Overall, the results suggest that sentiment affects the monthly returns on real assets, in addition to sentiment affecting stock market returns as documented in the existing literature.

Prompted by the referee's suggestion that net contracting and money committed may capture economic fundamentals rather sentiment, we follow the procedure outlined in Section 2.2 and construct sentiment indices excluding NC and MC from the sentiment proxy set[8]. We then run the OLS regressions given by Equations (14) and (15), and the results are reported in Table IV, Panel B. It can be observed that results are consistent, in terms of interpretation, signs and statistical significance, when compared to results given by sentiment indices made up by five proxies. We acknowledge that NC and MC are shipping industry specific proxies and have not been previously employed in the literature. Nevertheless, we detect no effect on the results when these are excluded from the sentiment proxy set.

3.2 PREDICTIVE REGRESSIONS FOR VESSEL PRICE CYCLE PHASES

To determine the relationship between sentiment and cycle phases, we use the logistic regression to obtain the probability of expansion for up to h=1, 2, 3, 4, 5, 6 months ahead. The

[8] Results are available from the authors upon request.

realized cycle phase $S_{i,t+h}$ takes the value 1 when in expansion and 0 when in contraction. We suppose that:

$$S^*_{i,t+h} = \alpha + \delta SENTI_t^{market^{\perp}} + \theta SENTI_{i,t}^{sector^{\perp}} + \gamma BB_{i,t} + u_{i,t+h}, \tag{16}$$

where the cycle phase approximation variable $BB_{i,t}$ reflects the current phase of the cycle. By construction, the method of identifying turning points (Section 2.3) does not provide the actual cycle phase at t, since the procedure takes into account a window of ± 5 months to identify a possible turning point at t. As such, $BB_{i,t}$ is included in the model to capture the persistence in the structure of the dependent variable. To construct $BB_{i,t}$, we calculate the cumulative returns ($CumR_{i,t,h}$) of the vessel price series for different horizons h: short-term (h = 1,2,3,4 months), medium-term (h = 5,6,7,8 months), and long-term (h = 9,10,11,12 months). For a month to qualify as an expansion (contraction), we apply the restriction that a combination of cumulative returns of 2 different horizons must be positive (negative). For all types of vessels, the combination which minimizes the error (7% on average) when approximating the actual cycle phase, is the 4- and 6-month cumulative returns. Therefore,

$$BB_{i,t} = \begin{cases} 1, & i.e., expansion, if\ CumR_{i,t,4} > 0\ and\ CumR_{i,t,6} > 0 \\ 0, & i.e., contraction, if\ CumR_{i,t,4} < 0\ and\ CumR_{i,t,6} < 0 \end{cases} \tag{17}$$

Finally, the error term $u_{i,t+h}$ follows the logistic distribution:

$$P_{i,t+h} = Prob\left(S_{i,t+h} = 1 \middle| S^*_{i,t+h}\right) = \frac{1}{1 + exp\left[-\left(\alpha + \delta SENTI_t^{market} + \theta SENTI_{i,t}^{sector} + \gamma BB_{i,t} + u_{i,t+h}\right)\right]} \tag{18}$$

[INSERT TABLE V HERE]

Table V presents the results for market and sector-specific sentiment and their significance in predicting cycle phases in the 4 sectors[9]. Market sentiment is statistically significant up to 6 months ahead and serves as a contrarian predictor of shipping cycle phases, i.e., high sentiment today indicates future periods of contraction and vice versa. Further, sector-specific sentiment appears to contain information about future cycle phases only for the panamax sector. The cycle phase approximation variable is also significant and its positive sign indicates that an expansion this month may lead to an expansion next month as well. We have also run logit regressions when sentiment indices are constructed by excluding NC and MC from the sentiment proxy set; and results[10] are consistent in terms of sign and statistical significance.

The R^2 of the 1-month ahead models ranges between 43.1% and 33.8%, while, the fit gradually decreases as we move to predictions for more than 2 months ahead. The goodness-of-fit can also be confirmed by the Hosmer-Lemeshow (1989) statistic being significant (p-values >5%). To assess the prediction performance of the models, we consider the Type I and Type II errors: Type I (II) error occurs when the model predicts contraction (expansion) and the actual phase is expansion (contraction). Thus, we analyze the percentage of observations correctly classified and misclassified by the models given a cut-off probability calculated as in Palepu (1986). In general, Type II errors are higher than Type I errors, implying a tendency of the models to underestimate contractions and overestimate expansions. The total error of the 1-month ahead models across sectors ranges from 14.69% to 22.73%.

[9] For each sector, we have also run the model comprising the total sentiment and the cycle approximation variable. For reasons of brevity, we do not report the results (available from the authors upon request) in the paper.

[10] Results are available from the authors upon request.

Succinctly, our empirical results point towards the importance of market sentiment as a contrarian indicator of future cycle phases in all four sectors, while sector-specific sentiment is only important for panamax sector. As stated earlier in the paper, the statistical significance of market sentiment may also imply the existence of sentiment contagion within the sectors of the dry-bulk market. This may be explained by the fact that companies normally operate across sectors, in addition to word of mouth sharing of information between shipowners within the market.

3.3 DATING COMPARISON METRIC

In addition to model 1 (see Equation18), we have considered restricted alternative models 2 and 3 comprising the total sentiment and the cycle approximation variable, and the cycle approximation variable only, respectively. To assess the accuracy of model 1 against models 2 and 3, we use the Quadratic Probability Score (QPS) of Diebold and Rudebusch (1989):

$$QPS_{i,t+h} = T^{-1} \times \sum_{t=1}^{T} 2 \times \left(P_{i,t+h} - S_{i,t+h}\right)^2 \tag{19}$$

where $P_{i,t}$ is given by Equation (18). The QPS ranges from 0 to 2, with a score of 0 corresponding to perfect fit to the cycle chronology (see Section 2.3). From Table V it is obvious that model 1 yields the lowest QPS values. When comparing models 1 and 2, the average improvement[11] in QPS ranges from 5.04% in the handymax sector to 0.25% in the capesize sector. The improvement is significantly larger when we evaluate models 1 and 3, and ranges from 18.99% in the panamax sector to 11.78% in the handysize sector.

[11] The improvement in QPS is calculated as the percentage difference between the QPS values of two models for each forecasting horizon. The mean across each sector is then taken to estimate the average improvement in QPS.

Consequently, taking into account the market and sector-specific sentiment improves the cycle dating fitness.

4. Sentiment as an Investment Timing Tool

In what follows, we investigate the use of sentiment in the investment decision process for the sale and purchase of second-hand vessels in the dry-bulk market[12]. For the trading simulation exercise we consider monthly data for the period September 1996 to September 2011, including second-hand vessel prices, time-charter rates, and operating expenses from Clarksons Shipping Intelligence Network, and the 3-month US T-bill rate from Thomson Reuters.

Our aim is to illustrate the importance of sentiment as a market timing tool rather than investigate different complex trading strategies. Hence, we choose to construct three simple strategies based on: i) the 1-month ahead probability forecast (F1) for vessel price cycle phases; ii) simple moving average (SMA) filters on $SENTI_t^{market^{\perp}}$ (we have performed the same analysis on $SENTI_{i,t}^{total^{\perp}}$ and $SENTI_{i,t}^{sector^{\perp}}$ but results are not reported in the paper since the strategy on $SENTI_t^{market^{\perp}}$ proved superior); and iii) simple buy and hold which we use as a benchmark for comparison purposes.

The first strategy is based on the 1-month ahead probability forecast generated by Equation (18), where a buy signal is generated as soon as the model predicts expansion and a sell signal when it forecasts contraction (the cut-off probability value is the same used in

[12] We have run linear (Granger, 1969) and nonlinear causality (Dicks and Panchenko, 2006) tests to check for time-series dependencies between the sentiment indices and vessel prices. The tests indicate that there is a two-way causality: vessel price changes depend on previous sentiment levels and vice versa. Since the sentiment indices are orthogonalized, the two-way causality can be attributed to investors being over-confident/pessimistic due to vessel price returns being high/low, respectively; and the fact that sentiment should not be regarded as a gift and as such is also affected by market factors (Schmeling 2009). Results are available from the authors.

Equation 18). For the moving averages trading strategy, we apply short and medium-term monthly SMAs (1-12 months) on $SENTI_t^{market^{\perp}}$ (for reasons of brevity, we report results only for the 1, 6, 8, 10 and 12 SMAs). For this strategy, the buy and sell signals are based on the SMA series crossover of the zero line: a crossover from below initiates a sell signal, while from above a buy signal, i.e., the rule is based on the contrarian nature of sentiment in the shipping market. Finally, the buy-and-hold strategy involves the investor buying the vessel and operating it throughout her economic life, in our case the sample period.

The performance of the strategies is simulated for the capesize, panamax, handymax and handysize sectors based on the expected 1-month return:

$$E_{i,t}(R_{i,t+1}) = \frac{D \times E_{i,t}(schPx_{i,t+1}) - schPx_{i,t} + E_{i,t}(OI_{i,t+1})}{schPx_{i,t}} - TC_{i,t+1}, \tag{20}$$

where D is the depreciation due to wear and tear from operating the vessel (0.5 percent/month)[13]; $E_{i,t}schPx_{i,t+1}$ is the expected second-hand vessel price at time $t+1$ for sector i, $E_{i,t}OI_{i,t+1}$ is the expected 1-month operating income generated by the vessel for sector i (calculated on a monthly basis as the difference between time-charter rates and operating expenses), and $TC_{i,t+1}$ is the transaction cost incurred at the purchase of the vessel (1 percent/transaction). We assume that, when investors hold no position in the market, funds are invested in the 3-month US T-bills. Finally, we impose short-selling restrictions.

[INSERT TABLE VI HERE]

Table VI, Panel A, presents the in-sample empirical simulation results of the trading strategies. Based on the annualized mean return (MR), standard deviation (SD) and Sharpe

[13] Depreciation is estimated as the average value decline between 5 and 10 year old vessels, over the sample period.

ratio (SR) reports, the F1 and SMA strategies outperform the buy-and-hold in all sectors. Overall, in terms of Sharpe ratios, SMA(12) produces the best results across sectors with the ratio ranging from 1.287 to 1.552. The F1 and SMA strategies not only increase returns by generating higher annualized mean returns of up to 22.7%, but also reduce the volatility of the investment, hence improving the Sharpe ratios.

For a more realistic way to assess the efficiency of the buy and sell signals of the different strategies, we further carry out an out-of-sample analysis for the period October 2004 to September 2011. To this end, we re-estimate the factor loadings to construct the total, market and sector-specific indices (see Section 2.2) using observations up to September 2004. For the F1 strategy, we estimate the model in Equation (18) using observations up to September 2004 and generate probability forecasts for October 2004. Similarly, the buy or sell signal of the SMA strategy for October 2004 is based on the monthly SMAs calculated in September 2004. The above procedure is repeated every month by applying a rolling window method.

Table VI, Panel B, shows the results for the out-of-sample performance of the different trading strategies. In terms of MR, SD and SR, the F1 and SMA strategies still outperform the buy-and-hold in all sectors. More specifically, in the capesize sector F1 yields the highest annualized return of 23.9%, whereas SMA(12) the highest Sharpe ratio of 1.494. F1 and SMA(12) generate respectively the highest annualized mean return of 24.1% and Sharpe ratio of 1.608 in the panamax sector. Finally, the SMA(6 and 12) (F1) strategy performs best in the handymax (handysize) sector with an annualized return of 23.1% (25.3%) and Sharpe ratio of 1.735 (1.784).

Overall, the trading simulation[14] shows that incorporating sentiment in the vessel investment/divestment timing decision can provide substantial gains. Investors can benefit from higher returns on their investment; while at the same time partially offset the highly volatile nature of the shipping industry.

4.1 REALITY CHECK

Despite the effective performance of the proposed F1 and SMA strategies, an important issue which needs to be addressed is that of data snooping. As pointed out by Sullivan et al. (1999) and White (2000), data snooping occurs when a dataset is used more than once for selection and inference purposes. When testing different strategies, data snooping can increase the probability of having satisfactory results purely to chance or the use of posterior information, rather than the superior ability of the alternative strategies.

To assess the performance of the trading strategies we employ the stationary bootstrap of Politis and Romano (1994) (see Sullivan et al., 1999; Alizadeh and Nomikos, 2007). For this, we repeatedly generate artificial time series (5,000 in total) for the six sentiment proxies over the period September 1996 to September 2004, construct the corresponding market sentiment index and estimate the model given in Equation (18). The forward-looking performance of each strategy is then tested for the period October 2004 to September 2011 using each bootstrapped sample. All trading strategies are implemented for each one of the 5,000 bootstrapped series, thus, generating a series of empirical distributions of mean returns and Sharpe ratios. The null hypothesis tested is that the performance of the F1 and SMA strategies is no better than the passive buy-and-hold strategy.

[14] We have also performed the trading simulation (incl. the bootstrap simulation outlined in Section 4.1) when sentiment indices are constructed by excluding NC and MC from the sentiment proxy set. We do not observe any effect on the results, and these are available from the authors upon request.

The bootstrap simulation results are presented in Table VI, Panel C. The statistics reported are: the annualized mean return; the standard error of mean returns; and the Sharpe ratio across the bootstrapped samples. In terms of annualized mean returns, the F1 strategy outperforms the other strategies in the capesize and handysize sectors, while the SMA(12) strategy is superior in the panamax and handymax sectors, consistent with the in-sample exercise in Panel A. Additionally, the SMA(12) strategy offers the best Sharpe ratios in all sectors. Typically, we can conclude that the proposed trading strategies significantly outperform the buy-and-hold benchmark. For instance, implementing the F1 or SMA(12) strategies in the capesize sector boosts mean returns and Sharpe ratios by factors of approximately 1.5 and 2.5, respectively.

Formal statistical tests are also conducted by considering the empirical confidence intervals for the mean returns and Sharpe ratios of the strategies in excess of the buy-and-hold (Table VI, Panel D). We construct 90% empirical confidence intervals for the excess performance based on the bootstrap simulations and test whether the excess MRs and SRs are significantly different from zero; the p-values[15] of the tests are also reported. The results for MRs in excess of the benchmark strategy show that no strategy achieves superior performance at conventional significance levels. However, F1 and SMA strategies provide a significant increase in Sharpe ratios compared to the buy-and-hold strategy, with the exception of the handysize sector; only SMA(12) is statistically better at 10% significance level in this market. Overall, the bootstrap simulation analysis corroborates that sentiment contains important information that can be used in the investment timing decision for the sale and purchase of second-hand vessels.

[15] The p-values are calculated as the ratio of frequency of occurrence of negative (one-tail test) excess MRs or SRs over the total number of simulations (5,000 replications). The null hypothesis is that there is no significant difference between the statistics.

5. Conclusion

In this paper, we consider shipping sentiment proxies that reflect market expectations, valuation and liquidity, and construct market and sector-specific sentiment indices for the capesize, panamax, handymax and handysize sectors of the dry-bulk market. We then examine the implications of sentiment for real assets of the economy, i.e., vessels; in particular, we study the use of sentiment as a predictor of vessel price returns. Sentiment is found to be statistically significant and a contrarian indicator of future vessel price returns on an individual sector basis and across all sectors. Our results add to those of the current literature, i.e., in addition to stock market returns, sentiment also affects the monthly returns on real assets.

Further, our analysis of the predictive power of sentiment for vessel price cycle phases suggests that market sentiment is a contrarian indicator in all sectors and sector-specific sentiment appears to be significant only in the panamax sector. The fact that market sentiment contains significant information for future vessel price returns and cycle phases implies the existence of possible cross-section sentiment contagion in the dry-bulk shipping market.

Finally, sentiment also plays an important role in the investment decision for the sale and purchase of second-hand vessels. A sentiment-based trading simulation exercise suggests that investors can benefit from higher annualized mean returns, while partially offsetting the highly volatile nature of the shipping industry.

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Table I. Correlation of index components and total sentiment indices

$SENTI_{i,t}^{total^{\perp}}$ is the first principal component of the five orthogonalized sentiment proxies for dry-bulk sector *i*. NC is the net contracting, MC the money committed, PE the price-to-earnings ratio, SNB the second-hand-to-newbuilding price ratio, and TURN the turnover ratio, defined in Section 2.1. The orthogonalized proxies labelled with $\perp$ are the residuals from the regression of each of the five raw sentiment proxies on the G7 industrial production growth and two-recession period dummies for the G7 and Major 5 Asia countries. Superscripts a, b, and c indicate significance at the 1%, 5% and 10% level, respectively.

	Correlations with $SENTI_{i,t}^{total^{\perp}}$	Correlations among proxies				
Capesize						
	$SENTI_{cape,t}^{total^{\perp}}$	$NC_{t-2}^{\perp}$	$MC_{t}^{\perp}$	$PE_{t-1}^{\perp}$	$SNB_{t-1}^{\perp}$	$TURN_{t-1}^{\perp}$
$NC_{t-2}^{\perp}$	0.73[a]	1.00				
$MC_{t}^{\perp}$	0.71[a]	0.31[a]	1.00			
$PE_{t-1}^{\perp}$	-0.48[a]	-0.28[a]	-0.29[a]	1.00		
$SNB_{t-1}^{\perp}$	0.84[a]	0.44[a]	0.49[a]	-0.26[a]	1.00	
$TURN_{t-1}^{\perp}$	0.82[a]	0.56[a]	0.43[a]	-0.18[b]	0.69[a]	1.00
Panamax						
	$SENTI_{pana,t}^{total^{\perp}}$	$NC_{t-2}^{\perp}$	$MC_{t}^{\perp}$	$PE_{t-1}^{\perp}$	$SNB_{t-2}^{\perp}$	$TURN_{t-1}^{\perp}$
$NC_{t-2}^{\perp}$	0.63[a]	1.00				
$MC_{t}^{\perp}$	0.80[a]	0.35[a]	1.00			
$PE_{t-1}^{\perp}$	-0.60[a]	-0.29[a]	-0.33[a]	1.00		
$SNB_{t-2}^{\perp}$	0.92[a]	0.45[a]	0.64[a]	-0.58[a]	1.00	
$TURN_{t-1}^{\perp}$	0.86[a]	0.43[a]	0.61[a]	-0.33[a]	0.78[a]	1.00
Handymax						
	$SENTI_{hmax,t}^{total^{\perp}}$	$NC_{t-2}^{\perp}$	$MC_{t}^{\perp}$	$PE_{t-1}^{\perp}$	$SNB_{t-2}^{\perp}$	$TURN_{t-2}^{\perp}$
$NC_{t-2}^{\perp}$	0.52[a]	1.00				
$MC_{t}^{\perp}$	0.77[a]	0.22[a]	1.00			
$PE_{t-1}^{\perp}$	-0.74[a]	-0.25[a]	-0.38[a]	1.00		
$SNB_{t-2}^{\perp}$	0.92[a]	0.40[a]	0.62[a]	-0.66[a]	1.00	
$TURN_{t-2}^{\perp}$	0.84[a]	0.40[a]	0.73[a]	-0.53[a]	0.79[a]	1.00
Handysize						
	$SENTI_{hsize,t}^{total^{\perp}}$	$NC_{t-2}^{\perp}$	$MC_{t}^{\perp}$	$PE_{t-1}^{\perp}$	$SNB_{t-2}^{\perp}$	$TURN_{t-2}^{\perp}$
$NC_{t-2}^{\perp}$	0.52[a]	1.00				
$MC_{t}^{\perp}$	0.74[a]	0.34[a]	1.00			
$PE_{t-1}^{\perp}$	-0.76[a]	-0.41[a]	-0.35[a]	1.00		
$SNB_{t-2}^{\perp}$	0.87[a]	0.52[a]	0.55[a]	-0.63[a]	1.00	
$TURN_{t-2}^{\perp}$	0.82[a]	0.45[a]	0.49[a]	-0.57[a]	0.65[a]	1.00

Table II. Correlation of total, market and sector sentiment indices

$SENTI_t^{market^\perp}$ is the first principal component of $SENTI_{cape,t}^{total^\perp}$, $SENTI_{pana,t}^{total^\perp}$, $SENTI_{hmax,t}^{total^\perp}$, $SENTI_{hsize,t}^{total^\perp}$. $SENTI_{i,t}^{sector^\perp}$ are the from regressing $SENTI_{i,t}^{total^\perp}$ on $SENTI_t^{SENTI_t^{market^\perp}}$ for each sector. Superscripts a, b, and c indicate significance at the 1%, 5% and 10% level respectively.

Panel A: Market and total sentiment indices

	Correlations with $SENTI_t^{market^\perp}$	Correlations among $SENTI_{i,t}^{total^\perp}$			
	$SENTI_t^{SENTI_t^{market^\perp}}$	$SENTI_{cape,t}^{total^\perp}$	$SENTI_{pana,t}^{total^\perp}$	$SENTI_{hmax,t}^{total^\perp}$	$SENTI_{hsize,t}^{total^\perp}$
$SENTI_{cape,t}^{total^\perp}$	0.94[a]	1.00			
$SENTI_{pana,t}^{total^\perp}$	0.97[a]	0.90[a]	1.00		
$SENTI_{hmax,t}^{total^\perp}$	0.99[a]	0.92[a]	0.96[a]	1.00	
$SENTI_{hsize,t}^{total^\perp}$	0.94[a]	0.80[a]	0.89[a]	0.91[a]	1.00

Panel B: Market, total and sector sentiment indices

	Correlations with $SENTI_t^{market^\perp}$ and $SENTI_{i,t}^{total^\perp}$		Correlations among $SENTI_{i,t}^{sector^\perp}$			
	$SENTI_t^{SENTI_t^{market^\perp}}$	$SENTI_{i,t}^{total^\perp}$	$SENTI_{cape,t}^{sector^\perp}$	$SENTI_{pana,t}^{sector^\perp}$	$SENTI_{hmax,t}^{sector^\perp}$	$SENTI_{hsize,t}^{sector^\perp}$
$SENTI_{cape,t}^{sector^\perp}$	0.00	0.34[a]	1.00			
$SENTI_{pana,t}^{sector^\perp}$	0.00	0.22[a]	-0.29[a]	1.00		
$SENTI_{hmax,t}^{sector^\perp}$	0.00	0.17[b]	-0.21[a]	-0.07	1.00	
$SENTI_{hsize,t}^{sector^\perp}$	0.00	0.35[a]	-0.56[a]	-0.35[a]	-0.26[a]	1.00

Table III. Dry-bulk vessel prices cycle phases statistics

The average duration ($\widehat{D}$) and amplitude ($\hat{A}$) are calculated according to Harding and Pagan (2001). The statistics are estimated based on incomplete phases; if statistics were calculated on complete phases, the summation should run from the beginning of the first completed phase until the end of the last one rather than over 1,..,*T*. The concordance index ($\hat{I}_{i,j}$) is estimated as proposed by Harding and Pagan (2002), and $\rho_{i,j}$ is the correlation coefficient estimated from the regression: $S_{j,t}/\sigma_{S_j} = \alpha + \rho_{i,j}\,(S_{i,t}/\sigma_{S_i}) + u_t$ where σ_S is the standard deviation of the cycle phase *S* (Harding and Pagan, 2006). Superscripts a, b, and c indicate significance at the 1%, 5%, and 10% respectively. The null hypothesis of no concordance between two series corresponds to $\rho_{i,j} = 0$, using robust standard errors; corrected for heteroscedasticity and serial correlation.

Panel A: Average duration and amplitude

	Expansion (trough-to-peak)		Contraction (peak-to-trough)	
	$\widehat{D}$ (months)	$\hat{A}$ (%)	$\widehat{D}$ (months)	$\hat{A}$ (%)
Capesize	23.8	0.568	13.8	-0.529
Panamax	22.8	0.632	14.8	-0.586
Handymax	26.5	0.678	20.5	-0.624
Handysize	22.4	0.513	15.2	-0.458

Panel B: Concordance index

	$^{capesize}/_{panamax}$	$^{capesize}/_{handymax}$	$^{capesize}/_{handysize}$	$^{panamax}/_{handymax}$	$^{panamax}/_{handysize}$	$^{handymax}/_{handysize}$
$\hat{I}_{i,j}$	0.724	0.665	0.838	0.930	0.789	0.741
$\rho_{i,j}$	0.431[a]	0.321[b]	0.684[a]	0.881[a]	0.627[a]	0.494[a]

Table IV. Vessel price returns, total, market and sector-specific sentiment indices

OLS regressions of next month vessel price returns on current month total sentiment (Equation 14) or on current month market sentiment and current month sector sentiment (Equation 15). Panel A provides results when sentiment is captured by five sentiment proxies (NC, MC, PE, SNB, TURN), and Panel B when sentiment is captured by 3 proxies (PE, SNB, and TURN). The last rows (named Dry-bulk) of Panels A and B present the results of the pooled regressions for the cross-section analysis. Bias-adjusted standard errors, given by the stationary bootstrap of Politis and Romano (1994), are in (.); Newey-West (1987) standard errors are in [.]. Superscripts a, b, and c indicate significance based on the bootstrapped standard errors at the 1%, 5% and 10% level, respectively.

$$R_{i,t+1} = \beta + \mu SENTI_{i,t}^{total^{\perp}} + u_{i,t+1} \qquad (14)$$

$$R_{i,t+1} = \rho + \phi SENTI_{t}^{market^{\perp}} + \omega SENTI_{i,t}^{sector^{\perp}} + u_{i,t+1} \qquad (15)$$

	β	μ	R^2	ρ	ϕ	ω	R^2
Panel A: NC and MC included							
Capesize	0.0020	-0.0100[b]	0.0425	0.0020	-0.0108[b]	0.0190	0.0882
	(0.0057)	(0.0049)		(0.0056)	(0.0047)	(0.0174)	
	[0.0059]	[0.0048]		[0.0073]	[0.0064]	[0.0136]	
Panamax	0.0021	-0.0116[b]	0.0547	0.0021	-0.0113[b]	-0.0129	0.0675
	(0.0062)	(0.0050)		(0.0062)	(0.0054)	(0.0269)	
	[0.0079]	[0.0062]		[0.0079]	[0.0065]	[0.0310]	
Handymax	0.0018	-0.0109[b]	0.0674	0.0018	-0.0107[b]	-0.0235	0.0876
	(0.0053)	(0.0048)		(0.0052)	(0.0045)	(0.0205)	
	[0.0071]	[0.0062]		[0.0069]	[0.0059]	[0.0197]	
Handysize	0.0021	-0.0095[c]	0.0651	0.0029	-0.0091[b]	-0.0117	0.0840
	(0.0046)	(0.0049)		(0.0049)	(0.0046)	(0.0072)	
	[0.0058]	[0.0059]		[0.0047]	[0.0025]	[0.0076]	
Dry-bulk	0.0018	-0.0104[a]	0.0552	0.0018	-0.0094[a]	-0.0040	0.0572
	(0.0028)	(0.0028)		(0.0027)	(0.0024)	(0.0128)	
	[0.0038]	[0.0039]		[0.0038]	[0.0028]	[0.0139]	
Panel B: NC and MC excluded							
Capesize	0.0017	-0.0142[b]	0.0585	0.0020	-0.0111[b]	0.0100	0.0775
	(0.0056)	(0.0061)		(0.0056)	(0.0046)	(0.0147)	
	[0.0079]	[0.0075]		[0.0076]	[0.0061]	[0.0183]	
Panamax	0.0019	-0.0155[b]	0.0695	0.0021	-0.0123[b]	-0.0051	0.0770
	(0.0061)	(0.0069)		(0.0061)	(0.0055)	(0.0186)	
	[0.0078]	[0.0080]		[0.0080]	[0.0065]	[0.0185]	
Handymax	0.0018	-0.0137[b]	0.0775	0.0018	-0.0106[b]	-0.0123	0.0829
	(0.0052)	(0.0059)		(0.0053)	(0.0045)	(0.0213)	
	[0.0071]	[0.0075]		[0.0071]	[0.0056]	[0.0264]	
Handysize	0.0022	-0.0103[c]	0.0534	0.0029	-0.0087[c]	-0.0026	0.0662
	(0.0049)	(0.0057)		(0.0047)	(0.0048)	(0.0098)	
	[0.0047]	[0.0032]		[0.0048]	[0.0025]	[0.0122]	
Dry-bulk	0.0018	-0.0128[a]	0.0603	-0.0018	-0.0099[a]	-0.0028	0.0634
	(0.0028)	(0.0030)		(0.0028)	(0.0023)	(0.0078)	
	[0.0038]	[0.0035]		[0.0038]	[0.0027]	[0.0105]	

Table V. Cycle phases, market and sector-specific sentiment indices

The table provides the logistic regression results of Equation (18) for each sector and horizons ($h = 1,..,6$). The Macfadden (1973) R^2 is reported; superscript * indicates that the Hosmer-Lemeshow (1989) test statistic is significant (*p-value*> 5%). Bias-adjusted standard errors, given by the stationary bootstrap of Politis and Romano (1994), are in (.). Superscripts a, b, and c indicate significance at the 1%, 5% and 10% level, respectively. Type I (II) error occurs when the model predicts contraction (expansion) and the actual phase is expansion (contraction); QPS is the quadratic probability score, with subscripts 1, 2, and 3 indicating respectively: $Prob\left(S_{i,t+h} = 1\middle|\alpha + \delta SENTI_t^{market} + \theta SENTI_{i,t}^{sector} + \gamma BB_{i,t} + u_{i,t+h}\right)$, $Prob\left(S_{i,t+h} = 1\middle|\alpha + \beta SENTI_t^{total} + \gamma BB_{i,t} + u_{i,t+h}\right)$ and $Prob(S_{i,t+h} = 1|\alpha + \gamma BB_{i,t} + u_{i,t+h})$

	α	δ	θ	γ	R^2	Type I Error (%)	Type II Error (%)	Total Error (%)	QPS[1]	QPS[2]	QPS[3]
Panamax											
$S_{i,t+1}$	-1.208[a]	-0.445[a]	0.672	3.481[a]	0.383*	19.33	22.41	20.34	0.245	0.257	0.274
	(0.413)	(0.142)	(0.519)	(0.619)							
$S_{i,t+2}$	-0.740c	-0.522[a]	0.902	2.700[a]	0.303*	26.89	24.56	26.14	0.288	0.310	0.337
	(0.394)	(0.156)	(0.569)	(0.585)							
$S_{i,t+3}$	-0.336	-0.498[a]	0.501	1.950[a]	0.208*	27.27	25.64	26.16	0.331	0.346	0.385
	(0.375)	(0.156)	(0.650)	(0.532)							
$S_{i,t+4}$	-0.337	-0.498[a]	0.715	1.466[a]	0.175*	28.21	25.45	27.33	0.345	0.367	0.406
	(0.399)	(0.164)	(0.698)	(0.550)							
$S_{i,t+5}$	0.232	-0.461[a]	0.409	0.972[c]	0.128	29.66	29.09	29.48	0.370	0.385	0.424
	(0.404)	(0.164)	(0.630)	(0.525)							
$S_{i,t+6}$	0.546	-0.440[a]	0.472	0.449	0.107	29.66	30.91	30.06	0.382	0.399	0.434
	(0.416)	(0.158)	(0.611)	(0.522)							
Panamax											
$S_{i,t+1}$	-1.579[a]	-0.551[a]	-2.218[b]	4.054[a]	0.431*	14.04	15.87	14.69	0.217	0.241	0.285
	(0.470)	(0.206)	(1.013)	(0.799)							
$S_{i,t+2}$	-0.997[b]	-0.527[a]	-1.533[c]	2.958[a]	0.306*	19.30	20.97	19.89	0.283	0.296	0.348
	(0.421)	(0.183)	(0.864)	(0.647)							
$S_{i,t+3}$	-0.625	-0.505[a]	-1.386[c]	2.225[a]	0.226*	24.78	25.81	25.14	0.327	0.337	0.395
	(0.399)	(0.179)	(0.822)	(0.573)							
$S_{i,t+4}$	-0.410	-0.557[a]	-2.108[a]	1.884[a]	0.219*	25.23	25.81	25.43	0.341	0.357	0.424
	(0.386)	(0.181)	(0.728)	(0.532)							
$S_{i,t+5}$	-0.123	-0.541[a]	-2.094[a]	1.366[a]	0.186*	26.79	27.42	27.01	0.360	0.377	0.444
	(0.373)	(0.180)	(0.702)	(0.502)							
$S_{i,t+6}$	0.170	-0.470[a]	-1.655[b]	0.800[c]	0.134*	30.00	30.65	30.23	0.386	0.399	0.458
	(0.369)	(0.170)	(0.639)	(0.481)							
Handymax											
$S_{i,t+1}$	-1.285[a]	-0.472[a]	-1.145	3.268[a]	0.338*	20.75	23.94	22.03	0.287	0.290	0.333
	(0.348)	(0.155)	(0.988)	(0.601)							
$S_{i,t+2}$	-0.963[a]	-0.488[a]	-0.668	2.648[a]	0.265*	25.47	27.14	26.14	0.330	0.330	0.380
	(0.339)	(0.157)	(0.937)	(0.542)							
$S_{i,t+3}$	-0.657[b]	-0.482[a]	-0.598	2.075[a]	0.203*	30.19	30.43	30.29	0.360	0.360	0.417
	(0.343)	(0.168)	(0.936)	(0.532)							
$S_{i,t+4}$	-0.359	-0.471[a]	-0.270	1.527[a]	0.153*	30.19	32.84	31.21	0.387	0.387	0.446
	(0.348)	(0.177)	(0.915)	(0.509)							
$S_{i,t+5}$	-0.135	-0.458[b]	-0.275	1.135[b]	0.124*	30.88	33.02	32.18	0.401	0.401	0.461
	(0.359)	(0.184)	(0.902)	(0.507)							
$S_{i,t+6}$	0.031	-0.429[b]	-0.089	0.848[c]	0.102*	33.02	33.33	33.14	0.413	0.415	0.468
	(0.359)	(0.179)	(0.847)	(0.493)							
Handysize											
$S_{i,t+1}$	-2.408[a]	-0.219[b]	-0.631	4.131[a]	0.424*	21.43	21.54	21.47	0.224	0.228	0.232
	(0.700)	(0.119)	(0.644)	(0.780)							
$S_{i,t+2}$	-1.705[a]	-0.239[b]	-0.587	3.282[a]	0.321*	25.89	26.56	26.14	0.278	0.281	0.298
	(0.552)	(0.132)	(0.610)	(0.659)							
$S_{i,t+3}$	-1.096[b]	-0.334[b]	-0.751	2.474[a]	0.242*	28.83	29.03	28.90	0.319	0.323	0.365
	(0.459)	(0.131)	(0.591)	(0.578)							
$S_{i,t+4}$	-0.642	-0.415[a]	-0.447	1.841[a]	0.176*	29.09	30.65	29.65	0.357	0.358	0.414
	(0.419)	(0.145)	(0.581)	(0.535)							
$S_{i,t+5}$	-0.392	-0.511[a]	-0.211	1.479[a]	0.163*	30.36	30.16	30.29	0.367	0.370	0.439
	(0.402)	(0.158)	(0.562)	(0.519)							
$S_{i,t+6}$	-0.094	-0.579[a]	-0.045	1.049[b]	0.155*	31.25	30.65	31.03	0.375	0.382	0.456
	(0.431)	(0.167)	(0.628)	(0.527)							

Table VI. Empirical simulation of trading strategies

F1 strategy is based on the 1-month ahead probability forecast given by Equation (18): a probability forecast indicating contraction (expansion) generates a sell (buy) signal. SMA denotes simple moving average strategies based on the $SENTI_t^{market\perp}$ crossover of the zero line: a crossover from below (above) initiates a sell (buy) signal. MR, SD and SR are the annualized mean return, standard deviation and Sharpe ratio for each strategy. Panel A reports the results for the whole sample, September 1996 to September 2011. Panel B shows simulation results where the period September 1996 to September 2004 is used for in-sample estimation, and the period October 2004 to September 2011 for out-of-sample testing. Panel C and D present the results of 5,000 realizations of the strategies based on the stationary bootstrap of Politis and Romano (1994). Panel C reports the average MR and SR across the 5,000 simulations, whereas SE stands for the estimated standard errors of the mean returns. Panel D provides the 90% empirical confidence intervals in brackets [.]; values in {.} are the p-values and measure the significance level for which one can reject a one-tail test of the null hypothesis: mean returns or Sharpe ratios of the proposed strategies are no different to the buy-and-hold. Note that for all bootstrapped simulations, estimation of the market sentiment index and the coefficients of the logit model (Equation 18) are repeated each time for the period September 1996 to September 2004; then the performance of each strategy is tested for the period October 2004 to September 2011.

	Capesize			Panamax			Handymax			Handysize		
Panel A: In sample empirical simulation of trading strategies												
	MR	SD	SR	MR	SD	SR	MR	SD	SR	MR	SD	SR
F1	0.223	0.185	1.206	0.196	0.177	1.109	0.223	0.176	1.269	0.227	0.139	1.632
SMA(12)	0.207	0.161	1.287	0.220	0.148	1.488	0.224	0.144	1.552	0.172	0.118	1.455
SMA(10)	0.208	0.163	1.277	0.220	0.149	1.481	0.215	0.146	1.475	0.161	0.113	1.424
SMA(8)	0.196	0.165	1.193	0.206	0.149	1.379	0.212	0.145	1.461	0.149	0.111	1.335
SMA(6)	0.170	0.176	0.963	0.170	0.157	1.082	0.170	0.133	1.274	0.132	0.107	1.237
SMA(1)	0.093	0.135	0.688	0.088	0.134	0.654	0.116	0.115	1.006	0.078	0.103	0.758
Buy-and-hold	0.129	0.267	0.482	0.097	0.273	0.354	0.130	0.248	0.524	0.115	0.213	0.538
Panel B: Forward looking empirical simulation of trading strategies												
	MR	SD	SR	MR	SD	SR	MR	SD	SR	MR	SD	SR
F1	0.239	0.169	1.415	0.241	0.164	1.471	0.227	0.135	1.678	0.253	0.142	1.784
SMA(12)	0.223	0.149	1.494	0.230	0.143	1.608	0.231	0.134	1.722	0.172	0.125	1.383
SMA(10)	0.211	0.149	1.423	0.214	0.139	1.541	0.220	0.132	1.666	0.151	0.120	1.256
SMA(8)	0.197	0.145	1.360	0.202	0.138	1.469	0.215	0.131	1.639	0.140	0.121	1.154
SMA(6)	0.193	0.147	1.310	0.203	0.137	1.478	0.226	0.130	1.735	0.148	0.117	1.262
SMA(1)	0.144	0.150	0.960	0.111	0.143	0.772	0.168	0.124	1.348	0.096	0.113	0.856
Buy-and-hold	0.101	0.301	0.334	0.074	0.320	0.232	0.129	0.286	0.452	0.138	0.263	0.524
Panel C: Bootstrap simulation of trading strategies – mean returns and Sharpe ratios												
	MR	SE	SR	MR	SE	SR	MR	SE	SR	MR	SE	SR
F1	0.217	(0.097)	1.232	0.208	(0.096)	1.224	0.215	(0.097)	1.331	0.170	(0.076)	1.169
SMA(12)	0.211	(0.095)	1.338	0.212	(0.089)	1.425	0.219	(0.088)	1.580	0.168	(0.060)	1.467
SMA(10)	0.207	(0.093)	1.321	0.207	(0.088)	1.401	0.214	(0.088)	1.557	0.162	(0.057)	1.421
SMA(8)	0.199	(0.089)	1.294	0.199	(0.085)	1.366	0.211	(0.086)	1.578	0.155	(0.054)	1.391
SMA(6)	0.184	(0.087)	1.200	0.181	(0.083)	1.204	0.195	(0.085)	1.454	0.147	(0.055)	1.330
SMA(1)	0.134	(0.072)	0.961	0.123	(0.066)	0.898	0.157	(0.066)	1.300	0.110	(0.047)	0.993
Buy-and-hold	0.134	(0.147)	0.498	0.111	(0.133)	0.405	0.149	(0.130)	0.591	0.134	(0.107)	0.656
Panel D: Bootstrap confidence intervals and p-values relative to the buy-and-hold strategy												
	10%	90%	Prob.	10%	90%	Prob.	10%	90%	Prob.	10%	90%	Prob.
Returns in excess of the buy-and-hold												
F1	[-0.021	0.193]	{0.173}	[-0.009	0.206]	{0.132}	[-0.015	0.145]	{0.158}	[-0.039	0.117]	{0.311}
SMA(12)	[-0.052	0.200]	{0.241}	[-0.018	0.216]	{0.138}	[-0.059	0.180]	{0.240}	[-0.079	0.136]	{0.339}
SMA(10)	[-0.057	0.195]	{0.265}	[-0.023	0.209]	{0.151}	[-0.062	0.172]	{0.251}	[-0.088	0.133]	{0.355}
SMA(8)	[-0.068	0.188]	{0.287}	[-0.029	0.204]	{0.176}	[-0.069	0.172]	{0.273}	[-0.099	0.131]	{0.394}
SMA(6)	[-0.090	0.178]	{0.327}	[-0.051	0.182]	{0.231}	[-0.094	0.153]	{0.319}	[-0.108	0.123]	{0.416}
SMA(1)	[-0.154	0.150]	{0.475}	[-0.125	0.148]	{0.434}	[-0.126	0.134]	{0.456}	[-0.141	0.086]	{0.564}
Sharpe ratios in excess of the buy-and-hold												
F1	[0.055	1.269]	{0.073}	[0.158	1.412]	{0.032}	[0.123	1.300]	{0.039}	[-0.075	1.228]	{0.174}
SMA(12)	[0.178	1.402]	{0.032}	[0.416	1.558]	{0.009}	[0.348	1.567]	{0.012}	[0.015	1.430]	{0.094}
SMA(10)	[0.148	1.391]	{0.033}	[0.404	1.527]	{0.009}	[0.341	1.513]	{0.009}	[-0.029	1.436]	{0.112}
SMA(8)	[0.106	1.373]	{0.004}	[0.368	1.518]	{0.005}	[0.370	1.521]	{0.005}	[-0.063	1.459]	{0.132}
SMA(6)	[0.048	1.271]	{0.068}	[0.226	1.351]	{0.021}	[0.265	1.396]	{0.012}	[-0.112	1.362]	{0.161}
SMA(1)	[-0.198	0.973]	{0.238}	[-0.109	0.992]	{0.177}	[0.123	1.217]	{0.040}	[-0.436	0.961]	{0.280}

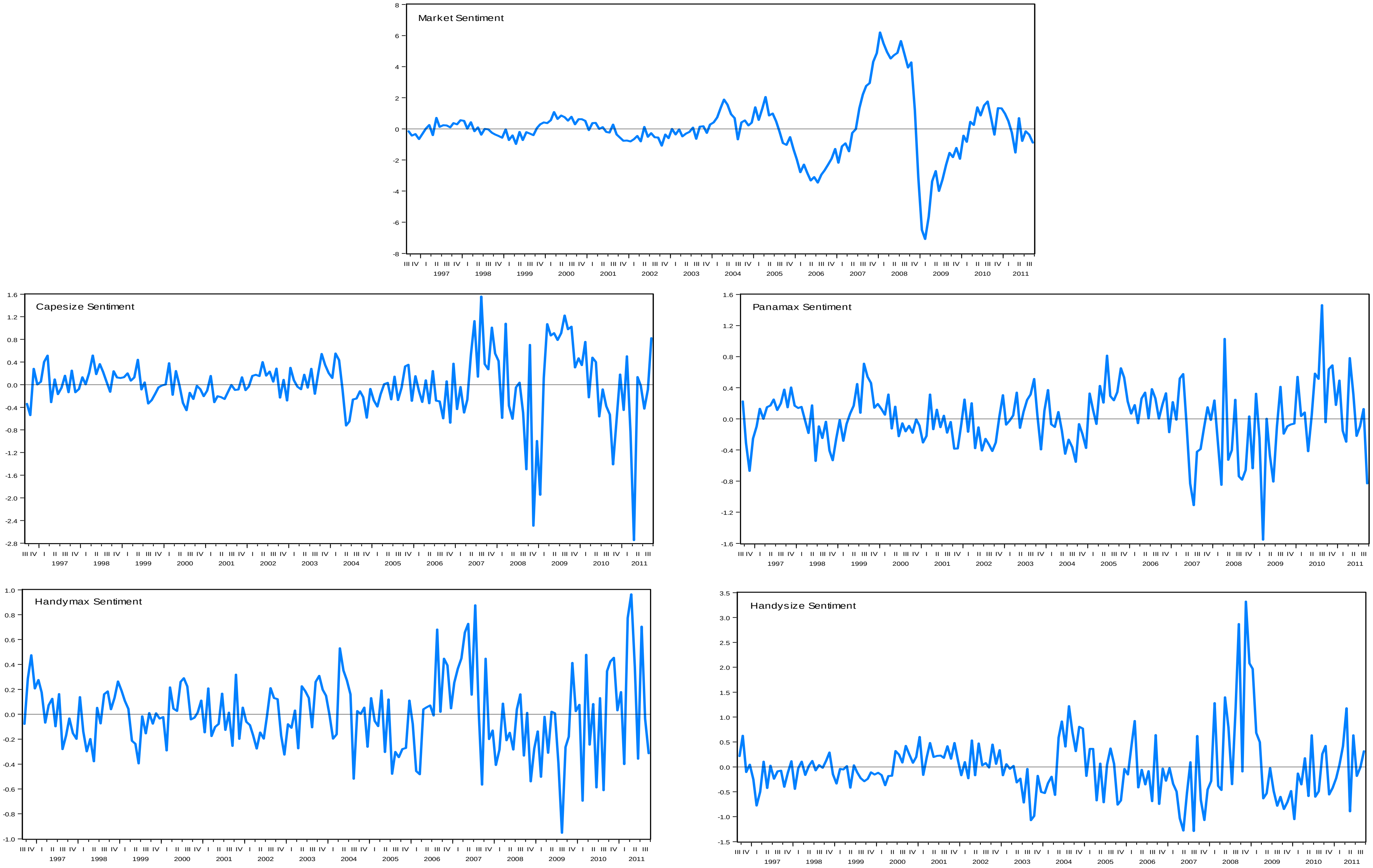

Figure 1. Market and Sector Sentiment Indices 1996-2011

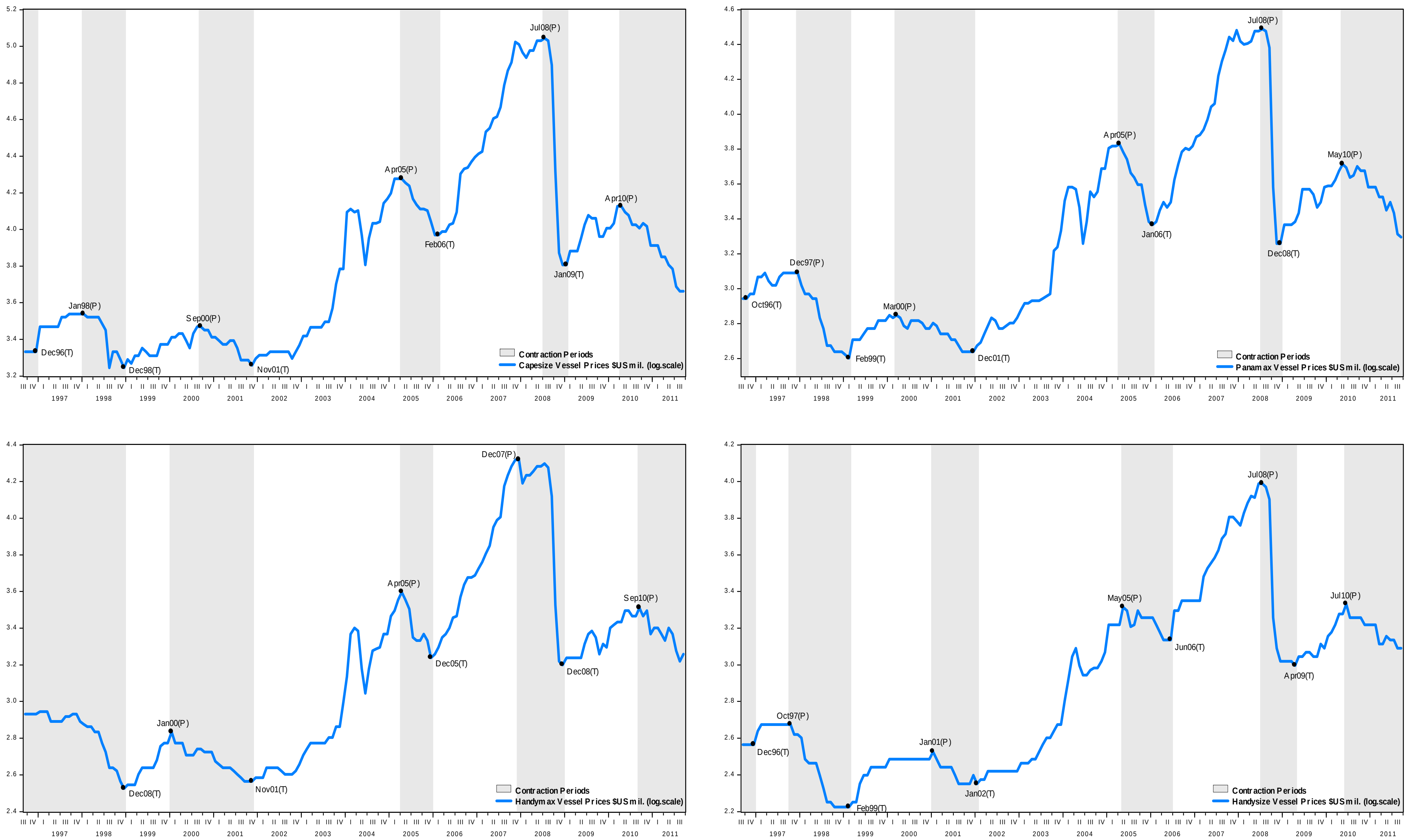

Figure 2. Turning Points of Vessel Prices 1996-2011 (P: Peak, T: Trough)

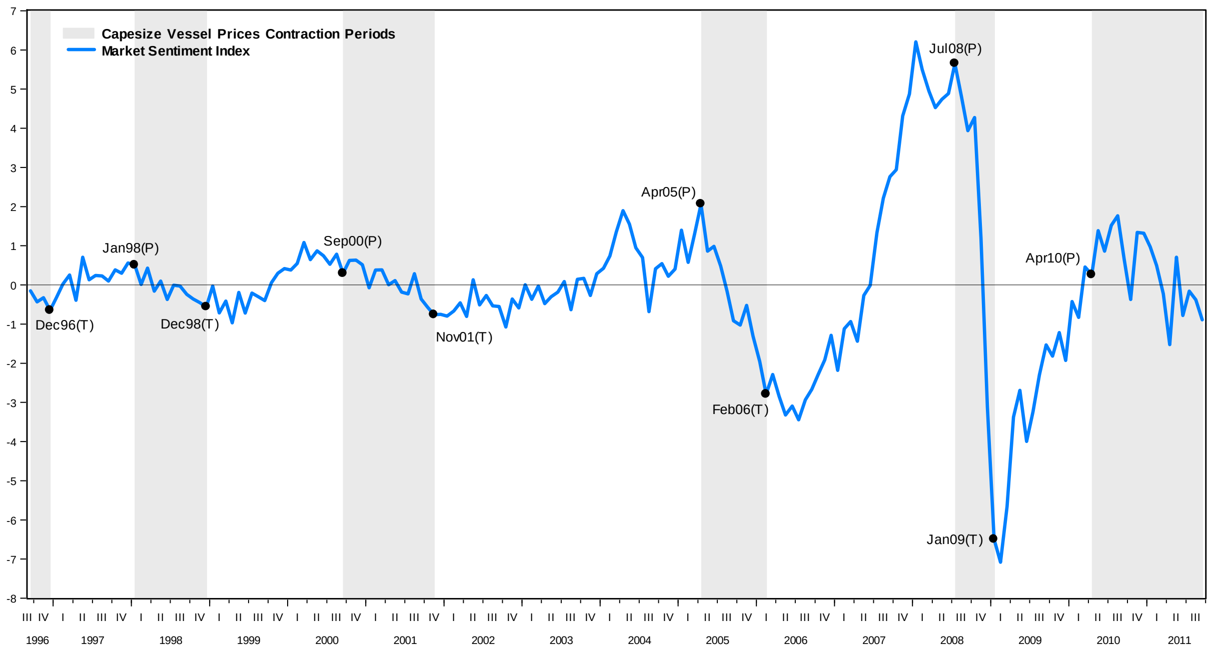

Figure 3. Market Sentiment and Capesize Vessel Prices Turning Points 1996-2011 (P: Peak, T: Trough)